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# A Framework for Evaluating Organizational Involvement in Online Ratings Communities

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## ABSTRACT

As online review systems become increasingly prevalent it is imperative for companies to evaluate their involvement in online ratings. Despite the widespread popularity of online ratings among consumers and firms alike, the business value that such systems bring to organizations, and the degree to which these organizations should be involved in filtering these reviews, remains unanswered questions. This paper addresses these questions by studying the relationship between a firm's online product ratings and the purchases made on their website. We find that the online ratings on a website are significantly correlated with online purchases. In addition, we find that a firms' filtering strategy for online reviews effects the impact of these ratings on purchases. The results of our work provide evidence that firms must think very carefully about their filtering policies for online reviews; the strategy that a firm implements in filtering their online reviews could indeed affect their bottom line.

## Keywords

Online ratings, online reviews, online word of mouth, online retailers, firm involvement, consumer information overload

## INTRODUCTION

One of the most intriguing social phenomena brought forth by advances in information and communication technologies is the vast amplification of the power of word-of-mouth. With the help of the Internet, wireless networking, and mobile telephony, today's citizens and consumers are forming a bewildering array of technology-mediated communities where they exchange opinions and experiences on companies, products, services, and even world events.

Word-of-mouth is arguably a phenomenon as old as society itself. Nevertheless, the advent of the Internet has added two important new dimensions to this timeless concept:

*Unprecedented scalability and speed of diffusion.* Information technologies enable opinions of a single individual to instantly reach thousands, or even millions of consumers. This escalation in audience is changing the dynamics of many industries in which word of mouth has traditionally played an important role. For example, the entertainment industry has found that the rapid spread of word of mouth is shrinking the lifecycles of its products and causing it to rethink its pre- and post-launch marketing strategies (Muñoz, 2003). In fact, movies are seeing much more rapid change in revenues between the opening weekend and second weekend, suggesting that public opinion is spreading faster<sup>1</sup>.

*Persistence and Measurability.* In offline settings word-of-mouth disappears into thin air. In online settings traces of word-of-mouth can be found in many publicly available Internet forums, such as review sites, discussion groups, chat rooms, and web logs. This public data provides organizations with the ability to quickly and accurately measure word-of-mouth *as it happens* by mining information available on Internet forums.

Rapid collection and measurement is the first prerequisite for the fast *reactions* that are needed in this new playing field. Nevertheless, the information value of online forums to organizations is currently not well understood. There is controversy related to the reliability of online reviews as well as to how well these reflect the opinions of the population of consumers. Anecdotal evidence suggests that some of this information may be biased and is sometimes provided anonymously by the companies themselves (White 1999; Harmon 2004). Finally, even though the impact of online reviews on consumer behavior

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<sup>1</sup> Rick Sands, the chief operating officer at Miramax, summarized this trend by stating that "In the old days . . . you could buy your gross for the weekend and overcome bad word of mouth, because it took time to filter out into the general audience. Those days are over. Today, there is no fooling the public" (Muñoz, 2003).

has been the focus of recent research (Chevalier and Mayzlin 2003; Senecal and Nantel 2003), there is very little work on how such information can be used by *firms* to gain business advantage.

This paper addresses firm involvement with online word of mouth data posted on their own site by studying the relationship of online reviews with product transactions before and after a company changed their policy for filtering reviews.

Our study provides affirmative answers to two important questions:

*Are online reviews correlated with online transactions?* We gathered data from a large online retailer regarding all of the reviews that are available on their site, as well as all of the transactions that occurred on the site in the same period that the reviews were available. The results provide evidence for the claim that online ratings are associated with online purchases.

*Does firm filtering of the online reviews effect the impact of these reviews on online transactions?* Online retailers have a wide range of approaches to filtering customer product reviews, with many struggling to find the correct balance. The retailer we study in this paper changed their filtering strategy and filtering team in March of 2005. We examine the impact of their reviews before and after the change in strategy to assess the difference in impact of the varying strategies of firm intervention. We find that firm's filtering strategy can impact which reviews (positive or negative) are significantly correlated with online transactions.

The rest of the paper is organized as follows. Section 2 discusses related work. Section 3 discusses our data set. Section 4 discusses our methodology. Section 5 presents the results. Section 6 discusses the results. Finally, Section 7 concludes and discusses the broader implications of this work.

## RELATED WORK

Our work relates and contributes to two important streams of past research: impact of word of mouth on sales and methodologies for measuring word-of-mouth.

*Impact of word of mouth on sales.* The impact of word of mouth on product sales was first examined by Bass (1969). The Bass model is a classic model of new product diffusion that incorporates the impact of mass media and interpersonal communication. The model has been shown capable of predicting the growth pattern of a wide range of new products with minimal data. The Bass model has spawned a huge literature of theoretical and empirical work. Many extensions to the model have been proposed. For excellent literature surveys see Mahajan et al. (1990; 2000).

*Methodologies for measuring word-of-mouth.* Traditional attempts to measure word of mouth are based on two principal techniques: inference and surveys. Bass (1969) used aggregated sales data to infer the coefficient of internal influence. Reingen et. al. (1984) infers that dense interpersonal communication occurs with women who live in the same residence. Surveys have been used more often, largely because individuals can specifically be asked about their communication habits (e.g. Bowman and Narayandas, 2001); the error then lies in the self-reporting of their behavior.

The advent of the Internet introduced a third technique for measuring word of mouth: directly through Usenet groups and feedback forums. Researchers can gather large amounts of data from online feedback forums. The use of such data, in combination with our extension of the Bass model, offers a low-cost alternative for making accurate predictions of revenue growth. Previous research has used *volume* and *dispersion* when measuring online word of mouth (Godes and Mayzlin, 2002). The theory behind measuring dispersion, or the spread of communication across communities, is that word of mouth spreads quickly within communities, but slowly across them (Granovetter, 1973). The theory behind volume is that the more consumers discuss a product, the higher the chance that other consumers will become aware of it. In this study we extend previous attempts to measure the impact of online word-of-mouth by experimenting with additional measures such as the *valence* (e.g. the average rating of a movie) and *number of extreme negative or extreme positive* (e.g. the number of reviews that were the worst rating (1 on a 1 to 5 scale), or the best rating (5 on a 1 to 5 scale)).

## DATA SET

Our data for this study consists of individual product characteristics and user reviews. These data were collected from a large online retailer, and the dates of the data range from April 16<sup>th</sup>, 1999 to February 2<sup>nd</sup>, 2006. The firm changed its reviews filtering method on March 3<sup>rd</sup> 2005. Accordingly, the overall data set is divided into two periods according to that date. Data of the first periods consist of transactions and reviews from April 16<sup>th</sup>, 1999 through March 3<sup>rd</sup> 2005, while data for the second period includes the entire available reviews and transactions from March 4<sup>th</sup> of 2005 through February 2<sup>nd</sup>, 2006.

The user reviews data consisted of an optional text review of product together with an integer numerical rating that ranged from 5 (best) to 1 (worst). Before these ratings are published on the online retailer's website, they go through a firm filtering

process, where all of the reviews re first market as pending (N for not yet rated), such that they are put in a queue to be approved or rejected by the review filtering team. As the team goes through the reviews, they either approve the reviews (T) or reject the reviews (F). From this review data we collect in each of the filtering categories: the average rating per product, the number of ratings per product, the standard deviation per product, the number of '1' ratings per product, and the number of '5' ratings per product.

## METHODOLOGY

The goal of this study is to generate a relationship between purchase activities and the review information, before and after the firm changed review filtering strategies. The dependent variables of purchase activities are represented by both two separate dependent variables: 1) Number of transactions; and 2) The amount spent per products. The independent variables include valence, defined as average rating at different stages (approved, pending, and rejected), numbers of '5' ratings, and number of '1' ratings, average number of words per review, current price per product, density metric, defined as the number of reviews divided by the total number of purchases, and a dummy variable controlling for the presence or absence of reviews.

Consider a product  $i$  that is sold on the public website. The product  $i$  belongs to the category  $j$  and the department  $k$ . Purchase activities are set up like the following:

Total number of purchases dependent variable:

$$\begin{aligned} \log(\text{number}_{i(j(k))}) = & \beta_{0-i(j(k))} + \beta_1 \log(\text{ave}_t) + \beta_2 \log(\text{ave}_f) + \beta_3 \log(\text{ave}_n) \\ & + \beta_4 \log(\text{num\_rev}_1) + \beta_5 \log(\text{num\_rev}_5) + \beta_6 \log(\text{num\_words}) + \beta_7 \log(\text{msrp}) \\ & + \beta_8 \log(\text{density\_metric}) + \beta_9 (\text{noreview\_dummy}) + \varepsilon_{i(j(k))} \end{aligned}$$

Total amount spent dependent variable:

$$\begin{aligned} \log(\text{spending}_{i(j(k))}) = & \beta_{0-i(j(k))} + \beta_1 \log(\text{ave}_t) + \beta_2 \log(\text{ave}_f) + \beta_3 \log(\text{ave}_n) \\ & + \beta_4 \log(\text{num\_rev}_1) + \beta_5 \log(\text{num\_rev}_5) + \beta_6 \log(\text{num\_words}) + \beta_7 \log(\text{msrp}) \\ & + \beta_8 \log(\text{density\_metric}) + \beta_9 (\text{noreview\_dummy}) + \varepsilon_{i(j(k))} \end{aligned}$$

Where "number" and "spending" are separate dependent variables of purchased number and total spending for the commodity  $i$ , "ave<sub>t</sub>", "ave<sub>f</sub>", and "ave<sub>n</sub>" are the average rating at variable stages, "num\_rev\_1" and "num\_rev\_5" are the number of reviews scoring 1 and 5, respectively. "num\_words" is the number of review words, "msrp" is the current price for the commodity, "density\_metric" is the density metric of the number of reviews divided by the number of purchases for the category, and "noreview\_dummy" is the dummy variable for no review scenario for the product.  $\varepsilon_{i(j(k))}$  is the random error for the product  $i$ . We adopt the constant elasticity modeling specification. We assume that the parameters of the average ratings are varying with the standard deviation of the corresponding rating. That is, we specify

$$\begin{aligned} \beta_1 &= \beta_1' + \gamma_1 \log(\text{std\_dev}_t) \\ \beta_2 &= \beta_2' + \gamma_2 \log(\text{std\_dev}_f) \\ \beta_3 &= \beta_3' + \gamma_3 \log(\text{std\_dev}_n) \end{aligned}$$

Plus, some unobservable characteristics across categories and departments are hypothesized to randomly influence the intercept  $\beta_{0-ijk}$ . That is,

$$\beta_{0-i(j(k))} = \beta_{0-i(j)} + \varepsilon_k,$$

$$\text{And } \beta_{0-i(j)} = \beta_{0-i} + \varepsilon_{j(k)},$$

$$\text{Therefore, } \beta_{0-i(j(k))} = \beta_0 + \varepsilon_k + \varepsilon_{j(k)}$$

After these adjustments, we set up the estimation function:

1) For the dependent variable of number of purchases

$$\begin{aligned} \log(\text{number}_{i(j(k))}) = & \beta_0 + \beta_1 \log(\text{ave\_t}) + \gamma_1 (\log(\text{ave\_t}) * \log(\text{std\_dev\_t})) \\ & + \beta_2 \log(\text{ave\_f}) + \gamma_2 (\log(\text{ave\_f}) * \log(\text{std\_dev\_f})) \\ & + \beta_3 \log(\text{ave\_n}) + \gamma_3 (\log(\text{ave\_n}) * \log(\text{std\_dev\_n})) \\ & + \beta_4 \log(\text{num\_rev\_1}) + \beta_5 \log(\text{num\_rev\_5}) + \beta_6 \log(\text{num\_words}) + \beta_7 \log(\text{msrp}) \\ & + \beta_8 \log(\text{density\_metric}) + \beta_9 (\text{noreview\_dummy}) + \varepsilon_{i(j(k))} + \varepsilon_{j(k)} + \varepsilon_k \end{aligned}$$

2) For the dependent variable of amount spent

$$\begin{aligned} \log(\text{spending}_{i(j(k))}) = & \beta_0 + \beta_1 \log(\text{ave\_t}) + \gamma_1 (\log(\text{ave\_t}) * \log(\text{std\_dev\_t})) \\ & + \beta_2 \log(\text{ave\_f}) + \gamma_2 (\log(\text{ave\_f}) * \log(\text{std\_dev\_f})) \\ & + \beta_3 \log(\text{ave\_n}) + \gamma_3 (\log(\text{ave\_n}) * \log(\text{std\_dev\_n})) \\ & + \beta_4 \log(\text{num\_rev\_1}) + \beta_5 \log(\text{num\_rev\_5}) + \beta_6 \log(\text{num\_words}) + \beta_7 \log(\text{msrp}) \\ & + \beta_8 \log(\text{density\_metric}) + \beta_9 (\text{noreview\_dummy}) + \varepsilon_{i(j(k))} + \varepsilon_{j(k)} + \varepsilon_k \end{aligned}$$

## RESULTS

The estimation results for the above specified model are as follows:

| Effect                | Estimate       | Standard Error  | t value       | Pr> t             |
|-----------------------|----------------|-----------------|---------------|-------------------|
| $\beta_0$             | <b>7.6552</b>  | <b>0.1495</b>   | <b>51.22</b>  | <b>&lt;0.0001</b> |
| <i>Ave_t</i>          | <b>0.09176</b> | <b>0.00191</b>  | <b>48.03</b>  | <b>&lt;0.0001</b> |
| <i>Ave_f</i>          | 0.000659       | 0.002157        | 0.31          | 0.7601            |
| <i>Ave_n</i>          | <b>0.07469</b> | <b>0.001935</b> | <b>38.6</b>   | <b>&lt;0.0001</b> |
| <i>Num_rev_1</i>      | 0.02035        | 0.02393         | 0.63          | 0.5259            |
| <i>Num_rev_5</i>      | <b>0.03195</b> | <b>0.002045</b> | <b>15.62</b>  | <b>&lt;0.0001</b> |
| <i>Num_words</i>      | 0.01691        | 0.008095        | 1.89          | 0.0589            |
| <i>Msrp</i>           | <b>-0.2245</b> | <b>0.009579</b> | <b>-23.44</b> | <b>&lt;0.0001</b> |
| <i>density</i>        | <b>0.09623</b> | <b>0.01978</b>  | <b>4.86</b>   | <b>&lt;0.0001</b> |
| <i>Noreview_dummy</i> | <b>-0.8739</b> | <b>0.114</b>    | <b>-7.66</b>  | <b>&lt;0.0001</b> |
| $\gamma_1$            | 0.04227        | 0.002705        | 15.63         | <0.0001           |
| $\gamma_2$            | 0.01636        | 0.00282         | 5.8           | <0.0001           |
| $\gamma_3$            | 0.07358        | 0.002623        | 28.05         | <0.0001           |

**Table 1. Number of purchases before the filtering strategy change**

| Effect           | Estimate       | Standard Error  | t value       | Pr> t             |
|------------------|----------------|-----------------|---------------|-------------------|
| $\beta_0$        | <b>9.5853</b>  | <b>0.1735</b>   | <b>55.24</b>  | <b>&lt;0.0001</b> |
| <i>Ave_t</i>     | <b>0.11</b>    | <b>0.00363</b>  | <b>30.3</b>   | <b>&lt;0.0001</b> |
| <i>Ave_f</i>     | <b>0.4732</b>  | <b>0.004083</b> | <b>115.92</b> | <b>&lt;0.0001</b> |
| <i>Ave_n</i>     | <b>0.01791</b> | <b>0.003815</b> | <b>4.69</b>   | <b>&lt;0.0001</b> |
| <i>Num_rev_1</i> | <b>0.04785</b> | <b>0.004345</b> | <b>11.01</b>  | <b>&lt;0.0001</b> |
| <i>Num_rev_5</i> | <b>0.02205</b> | <b>0.003814</b> | <b>5.78</b>   | <b>&lt;0.0001</b> |

|                       |                |                |               |                   |
|-----------------------|----------------|----------------|---------------|-------------------|
| <i>Num_words</i>      | <b>-0.1492</b> | <b>0.01657</b> | <b>-9</b>     | <b>&lt;0.0001</b> |
| <i>Msrp</i>           | <b>-0.276</b>  | <b>0.01652</b> | <b>-16.7</b>  | <b>&lt;0.0001</b> |
| <i>density</i>        | <b>-1.1277</b> | <b>0.06032</b> | <b>-18.69</b> | <b>&lt;0.0001</b> |
| <i>Noreview_dummy</i> | 0              | .              | .             | .                 |
| $\gamma_1$            | 0.1526         | 0.005371       | 28.41         | <0.0001           |
| $\gamma_2$            | 0.2346         | 0.004388       | 53.46         | <0.0001           |
| $\gamma_3$            | -0.00763       | 0.005277       | -1.45         | 0.1481            |

**Table 2. Number of purchases after the filtering strategy change**

There are two main differences that we see in the results across Table 1 and Table 2 as a result of the change in filtering strategy. Before the change the number of '1' ratings were not significantly associated with number of purchases. In addition, before the change, the average valence of the rejected reviews did not significantly affect the number of purchases, however, after the filtering strategy change; the average valence of the rejected reviews does significantly affect the number of purchases per product. In addition, after the change, the average valence of the rejected reviews did affect the number of purchases. Both of these results suggest that information was being lost in the filtering strategy implemented before the change. Consequently, after the change, when the firm was allowing negative reviews to surface, these reviews with negative ratings started to have a significant impact on the number of purchases. The significant result of the rejected reviews after the change, suggests that the information in the rejected reviews was similar to that in the approved reviews, and thus still had a significant effect on the number of purchases. Similar results were found with the dependent variable amount spent on purchases, thus, for the sake of readability, we omit those tables.

## DISCUSSION

Our initial results suggest several important issues. First, our results show positive support that online ratings are significantly associated with actual transactions. While previous studies have inferred a relationship between ratings and sales through sales rank (Chevalier and Mayzlin, 2003), we are the first study to show such a direct link through actual transaction data. In addition, our paper is the first to begin to examine firm involvement in online ratings. Specifically, we examine the impact of online ratings on sales across two different firm filtering strategies. Before March 3, 2005, the firm's filtering strategy was to filter out all reviews that reflected negatively on the firm or their products in any way. Thus the firm's filter was done by the marketing department, and the goal was to only keep reviews that would enhance sales. After March 3, 2005, the filtering was moved to the online experience department. The strategy of filtering changed to one of "noise reduction". Thus, reviews were filtered out only if they were deemed to provide no value (positive or negative). As such, comments including profanities, or comments not having to do with the product were filtered. The change in filtering strategies resulted in slightly different impacts of reviews on purchases. The significant impact of low ratings after the strategy change illustrated that low ratings were not being published online, and as such, were not associated with sales. The significant result of the rejected reviews after the change shows that the information in the rejected reviews after the change was similar to the information provided in approved reviews, which was not the case before the filtering strategy change. Thus, a firm's filtering strategy may impact the relationship between online ratings and sales.

## CONCLUSION

Online review sites are widespread on the Internet and rapidly gaining in popularity among consumers. Nevertheless, the business value of such information systems to organizations is still in the nascent stages of being established. This paper studies the relationship of online product reviews and ratings to online transaction on a large online retailer website. In addition, the paper examines how this relationship differs when the firm changes its strategy for filtering the reviews that are posted on their website. The contributions of this paper are two fold: First, this is one of the first papers to assess the relationship between online word of mouth and actual online transaction data (rather than inferred online sales). Second, this paper is one of the first to examine firm involvement in filtering of reviews posted on an online retailer site. Our study therefore provides affirmative answers to two important questions. First, we provide evidence for the claim that online ratings are associated with online product transactions and sales. We examined the correlation, on a product level over time, of various metrics of online ratings and reviews, and their association with the number of purchases and the amount of money spent. The ratings exhibited a positive and significant correlation with product transactions, thus validating a positive relationship between presence of online ratings and increased purchases. Second, we provide evidence that firm filtering

strategies can impact the relationship between online ratings and online transactions. Thus, by providing unbiased filtering companies actually increase the positive impact of online reviews on online transactions.

Apart from encouraging firms to include online reviews in their online retail experiences, we believe that the initial findings presented in this paper have the potential to play a role in firm information filtering strategy. Information overload has been heralded as one of the biggest issues for firms to cope with in this new “information age” (Berghel, 1997). Firms offer a service to their consumers by filtering out the noise in their online reviews so as to reduce consumer information overload. However, the way in which firms filter their reviews can affect the relationship between the reviews and the online transactions that occur on their site. Thus, firms must be cognizant of the potential impacts of their filtering strategies, as their chosen strategy will likely affect their bottom line.

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